Spatiotemporal models highlight influence of oceanographic conditions on common dolphin bycatch risk in the Bay of Biscay

Lola Gilbert
Bycatch on the rise
Mannocci et al. 2012

CONTEXT – BYCATCH THREAT

• Bycatch on the rise

• Represent a potent threat for the population
CONTEX – BYCATCH THREAT

• Bycatch on the rise

• Represent a potent threat for the population

• 1000 individuals/year → extinction in a 100 years
• Bycatch on the rise

• Represent a potent threat for the population

• 1000 individuals / year ➔ extinction in a 100 years

• Estimation for 4 months in 2019: 11,300 individuals (IC95%: [7550; 18,530])

Mannocci et al. 2012, Peltier et al. 2019
• In the Bay of Biscay, stranding data have been instrumental to study the issue
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➔ Estimations of its magnitude
In the Bay of Biscay, stranding data have been instrumental to study the issue:

- Estimations of its magnitude
- Spatio-temporal patterns
In the Bay of Biscay, stranding data have been instrumental to study the issue.

- Estimations of its magnitude
- Spatio-temporal patterns
- Possible association with dolphin preys

Is there an influence of oceanographic processes on the cooccurrence of and ?
HYPOTHESIS

Oceanographic processes structure the availability of preys.
HYPOTHESIS

Oceanographic processes structure the availability of preys.

Spatial

Temporal
HYPOTHESIS

Oceanographic processes structure the availability of preys.

Spatial

Temporal
• Circulation model

García-Barón et al. 2020, Tew-Kaï et al. 2020
- Circulation model

García-Barón et al. 2020, Tew-Kaï et al. 2020
OCEANOGRAPHIC

• Circulation model

BYCATCH MORTALITY

• Strandings → reverse drift

García-Barón et al. 2020, Tew-Kaï et al. 2020
- Circulation model

- Strandings $\rightarrow$ reverse drift

García-Barón et al. 2020, Tew-Kaï et al. 2020

M & M - DATASET

OCEANOGRAPHIC

- Circulation model

BYCATCH MORTALITY

- Strandings → reverse drift

García-Barón et al. 2020, Tew-Kaï et al. 2020

M & M – MORTALITY INDEX (MI)
Reverse drift modelling (MOTHY)
\[
\frac{\text{Nb of drift points of } i \text{ in pixel } s}{\text{Total nb of drift points of } i}
\]
\[
\frac{\text{Nb of drift points of } i \text{ in pixel } s}{\text{Total nb of drift points of } i}
\]
\[
\sum_i \frac{\text{Nb of drift points of } i \text{ in pixel } s}{\text{Total nb of drift points of } i}
\]
\[ \frac{\sum_{d} \sum_{i} \text{Nb of drift points of } i \text{ in pixel } s}{\text{Total nb of drift points of } i} \]
M & M – MORTALITY INDEX (MI)

\[
\frac{\sum_{d} \sum_{i}}{\text{Total nb of drift points of } i}
\]

\text{Nb of drift points of } i \text{ in pixel } s

→ Spatial

→ Temporal (month)
M & M – MORTALITY INDEX (MI)

→ Mortality areas

→ Intensity of mortality events
• 3 oceanographic variables

- Sea surface temperature (sst)
- Eddy kinetic energy (eke)
- Mean sea surface temperature gradient (mean_sst_grad)
• Spatiotemporal hierarchical bayesian model
• Spatiotemporal hierarchical bayesian model

• 1 model per month, each with 7 years

2012 ... 2018
• Spatiotemporal hierarchical bayesian model

• 1 model per month, each with 7 years

$$\log(MI_{s,t} + 1) \sim \mathcal{N}(\pi_{s,t}, \sigma)$$

$$Id(\pi_{s,t}) = \gamma \times SP_{s,t} + \beta_{0,t} + \sum_j \beta_{j,t} \times X_{j,s,t} + \eta_s + \epsilon_{s,t}$$
• Spatiotemporal hierarchical bayesian model

• 1 model per month, each with 7 years

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\]
MODELLING – HBMs WITH INLA

- Spatiotemporal hierarchical bayesian model
- 1 model per month, each with 7 years

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Covariates
• Spatiotemporal hierarchical bayesian model

• 1 model per month, each with 7 years

\[\log(MI_{s,t} + 1) \sim \mathcal{N}(\pi_{s,t}, \sigma)\]

\[Id(\pi_{s,t}) = \gamma \times SP_{s,t} + \beta_{0,t} + \sum_j \beta_{j,t} \times X_{j,s,t} + \eta_s + \epsilon_{s,t}\]
• Spatiotemporal hierarchical bayesian model

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\log(\text{MI}_{s,t} + 1) \sim \mathcal{N}(\pi_{s,t}, \sigma)
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\text{Id}(\pi_{s,t}) = \gamma \times SP_{s,t} + \beta_{0,t} + \sum_j \beta_{j,t} \times X_{j,s,t} + \eta_s + \epsilon_{s,t}
\]

Random intercept

Yearly linear coefficients (random slopes)

Covariates
MODELLING – HBMs WITH INLA

- Spatiotemporal hierarchical bayesian model

- 1 model per month, each with 7 years

\[ \log\left(\frac{MI_{s,t}}{1} + 1\right) \sim \mathcal{N}(\pi_{s,t}, \sigma) \]

\[ I_d(\pi_{s,t}) = \gamma \times SP_{s,t} + \beta_{0,t} + \sum_j \beta_{j,t} \times X_{j,s,t} + \eta_s + \epsilon_{s,t} \]

- Stranding probability
- Random intercept
- Yearly linear coefficients (random slopes)
- Covariates
• Spatiotemporal hierarchical bayesian model

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\log(MI_{s,t} + 1) \sim \mathcal{N}(\pi_{s,t}, \sigma)
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\]

- Stranding probability
- Random intercept
- Yearly linear coefficients (random slopes)
- Covariates
- Spatial field

MODELLING – HBMs WITH INLA
• Conditional autoregressive spatial field (CAR)

Besag et al. 1991, Besag & Kooperberg 1995
• Conditional autoregressive spatial field (CAR)
• 12 models: from January to December
• 12 models: from January to December

• 1 coefficient estimated / month and / year / covariate
12 models: from January to December

- 1 coefficient estimated / month and / year / covariate
- 1 spatial field estimated / month
12 models: from January to December

1 coefficient estimated / month and / year / covariate

1 spatial field estimated / month

INLA

Integrated
Nested
Laplace
Approximations

• Model selection based on WAIC
• Model selection based on WAIC

• Model evaluation:

  → Cross validation: prediction of MI for year 2019
• Model selection based on WAIC

• Model evaluation:

  ➔ **Cross validation**: prediction of MI for year 2019

  ➔ **Repetition scenarios**: prediction of MI for year 2019 with the index for covariates random slopes from previous years

Wanatabe 2010, Gelman et al. 2013
MODELLING – HBMsWith INLA

• Model selection based on WAIC

• Model evaluation:

  ➔ Cross validation: prediction of MI for year 2019

  ➔ Repetition scenarios: prediction of MI for year 2019 with the index for covariates random slopes from previous years

Could oceanographic processes’ effect on bycatch mortality help explain observed mortality of 2019?

Wanatabe 2010, Gelman et al. 2013
RESULTS – COVARIATES

The figure shows the posterior mean for eke, mean_sst_grad, sst, and intercept for different years (2012-2018) across months. The x-axis represents the months from 1 to 12, and the y-axis represents the posterior mean values. The graphs illustrate the variation in each covariate over the years.
• Seasonality
• Seasonality
• Inter-annual variability
• Inter-annual variability

High-frequency processes

Low frequency process

RESULTS – COVARIATES
• Between month variability
• **Variance** taken into account by the different components of the models

![Graph showing proportion of variance accounted for by different components over months.](image_url)
RESULTS – FITTED VS OBSERVED TOTAL MI

\[ \sum_s M_{Is} = \text{total nb of stranded carcasses for a month} \]
\[
\frac{\text{Nb of drift points of } i \text{ in pixel } s}{\text{Total nb of drift points of } i}
\]
• $\sum_s MI_s = \text{total nb of stranded carcasses for a month}$
RESULTS – CROSS-VALIDATION & REPETITION SCENARIOS

Cross-validation

Prediction for 2019: CV and RS

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Graph</th>
</tr>
</thead>
<tbody>
<tr>
<td>CV - 2019 = 2019</td>
<td></td>
</tr>
<tr>
<td>RS - 2019 = 2012</td>
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<td>RS - 2019 = 2013</td>
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Mean values vs Month

- Observed MI
- Predicted MI
RESULTS – CROSS-VALIDATION & REPETITION SCENARIOS

Repetition scenarios

Prediction for 2019: CV and RS

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- Observed MI
- Predicted MI

Month
RESULTS – CROSS-VALIDATION & REPETITION SCENARIOS

Prediction for 2019: CV and RS

- CV - 2019 = 2019
- RS - 2019 = 2012
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Mean values vs. Month

- Observed MI
- Predicted MI

Repetition scenarios

2013

2017
DISCUSSION - LIMITS

• Strandings → only minimal estimates of bycatch mortality
DISCUSSION - LIMITS

- Strandings ➔ only minimal estimates of bycatch mortality

- Models accounted for a low proportion of MI’s variance
DISCUSSION - LIMITS

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Indirect link
DISCUSSION - LIMITS

- Strandings only minimal estimates of bycatch mortality

- Models accounted for a low proportion of MI's variance

Indirect link – complex processes
DISCUSSION - LIMITS

• Strandings → only minimal estimates of bycatch mortality

• Models accounted for a low proportion of MI’s variance

• Models reproduced the overall mortality pattern ✔
DISCUSSION - LIMITS

- Strandings ➔ only **minimal estimates** of bycatch mortality

- Models accounted for a **low proportion** of MI’s **variance**

- Models reproduced the overall mortality pattern  

- Cross-validation  

  ✔️

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DISCUSSION - LIMITS

- Strandings only minimal estimates of bycatch mortality

- Models accounted for a low proportion of MI’s variance

- Models reproduced the overall mortality pattern

- Cross-validation

INLA
• Environnement & species distribution’s are highly dynamic

Test shorter time resolution
**DISCUSSION – PROSPECTS OF IMPROVEMENT**

- Environnement & species distribution’s are highly dynamic
  - Test shorter time resolution

- Focus on extreme mortality events
• Random slopes for covariates
• Random slopes for covariates

• Unique spatial field per month
• Random slopes for covariates

• Unique spatial field per month

• One model per month
• Random slopes for covariates

• Unique spatial field per month

• One model per month
Thank you!